# Modeling Temperature Dynamics for Aquaculture Index Insurance in Taiwan: A Nonlinear Quantile Approach

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**Extended Abstract**

According to the Taiwan Council of Agriculture, frost was responsible for approximately 30 percent of aquaculture losses in Taiwan during the period 1999-2008. Farmed milkfish, the most important aquaculture crop in Taiwan, is particularly sensitive to temperature variations, and can experience widespread kills whenever temperatures fall below 14°C for sustained periods of time. Temperatures below this critical minimum, however, are not uncommon during the January-March winter months.

The purpose of our study is to analyze the possible benefits and the actuarial properties of temperature-based index insurance for the farmed milkfish industry in Kaohsiung County, Taiwan. Weather-based index insurance has been promoted as a cost-effective means of managing risk associated with catastrophic weather events, examples of which include risk transfer products as varied as rainfall insurance in Mali and El Nino-Southern Oscillation insurance in Peru. Of special interest here will be performing accurate assessments of the actuarial properties of a temperature index contract that would indemnify Kaohsiung County farmed milkfish producers based on the value of lower-quadrant daily temperature, which has been shown to be highly correlated with extreme production losses.

To assess the actuarial properties of such a contract, we will develop a time series model of daily temperatures lows in Kaohsiung County. Daily temperatures exhibit some special features that must be observed by any reasonable time series model. For example, daily temperatures exhibit strong seasonality with small perturbations. Moreover, seasonal variations exist not only with the mean daily temperatures, but also their variance. Specifically, daily low temperatures are more volatile in winter than in summer.

To capture the special features of daily temperatures, we estimate a nonlinear nonstructural time series model of the quantiles of the conditional distribution of daily temperature lows given the observed covariates based on Campbell and Diebold (2005). A simple low-ordered polynomial function is used to capture the deterministic trend and autoregressive lags are used to capture cyclical dynamics of the daily temperature. Also, a Fourier series is applied to model the seasonal components in daily temperature and its variance. However, in contrast to Campbell and Diebold (2005), we model and forecast the lower quantile rather than mean of the daily temperature. We also introduce a phase angle in the low-order Fourier series to allow the peak of daily average temperature to occur at any point in time within a year. The algorithm for computing the nonlinear quantile regression estimates is based on an interior point method described in Koenker and Park (1996). Once the estimates are computed, we invoke bootstrap methods to compute confidence intervals for the contract's fair premium rate.

Our research employs 1974-2008 daily surface temperature data, which is collected and published by Central Bureau, Taiwan, for a weather station located in Kaohsiung County. The farmed milkfish production data in Kaohsiung County also obtained from Council of Agriculture, Executive Yuan, is used to examine the risk-reduction effectiveness of the temperature contracts with different trigger and stop-loss points. The contribution of our paper is not only to provide an alternative method in modeling temperature risk, but also to provide an empirical basis for further, more general discussion regarding the potential benefits of weather index insurance contracts in Taiwan.

**Key Words**: nonlinear quantile, temperature risk, weather index insurance

**Subject Code**: Agricultural Finance & Farm Management

It is well recognized that Taiwan agricultural and aquaculture industries have been adversely influenced by climate variability and weather extreme. The sensitivity of production to weather risks has suggested the demand for some forms of risk management tool. Despite government disaster assistance, there are few risk management alternatives available to Taiwanese agricultural and aquaculture producers. For example, the natural disaster aid funded by Taiwanese government only accounts for 15% of total losses caused by disastrous natural hazards during the period of 1991-2008, without accounting for low-rate loans for agricultural nature disasters provided by Taiwanese government (Council of Agriculture, Executive Yuan). The lack access to formal insurance and derivative markets for the management of production risk in Taiwan has been an important issue.

The weather risk market has been introduced only for a decade in the globe but has experienced a rapid evolution in recent years due to a growing consensus that Earth's climate is changing. This market manages weather risks in ways compatible with financial and insurance markets and receives increasing attentions from investors, researchers and policymakers due to its special features (Weather Risk Management Association). For example, rainfall insurance has been introduced in the United States as an alternative to multi-peril crop insurance product.

Unlike the traditional crop insurance contract, the weather insurance contract pays indemnity based on the value of specified climate index rather than individual farmer's actual losses. The index can be any objectively observable weather variable that is highly correlated with losses and that cannot be influenced by the insured. In other words, such weather insurance scheme requires no individual farmer data but an objectively observable climate index, which not only improves the actuarial measurement

of insurance premium rate but reduces program administrative costs. Also, since the contract payout is not relevant to individual production, the insured loses the incentive to alter their production practices to increase the expected indemnities. The problem of moral hazard and loss adjustment costs are therefore eliminated. However, weather insurance contracts cannot cover losses perfectly and must be carefully designed to provide maximum risk protection. Also, it is far more complex to model underlying process of weather variables.

In this paper, we are interested in exploring the feasibility of weather insurance contract in Taiwan. According to Council of Agriculture, Executive Yuan, frost damages has contributed to approximate 30 percent of aquaculture losses for the period of 1999-2008. Given that milkfish is an important aquaculture species to the aquaculture industry in Taiwan, we undertake a case study of Kaohsiung County farmed milkfish and propose a weather insurance contract that would provide farmed milkfish producers in Kaohsiung County with protection against production losses caused by frost damages. In particular, we propose a temperature-based insurance scheme, which would indemnify Kaohsiung County farmed milkfish producers based on the value of daily average temperature that is highly correlated with production losses.

Figure 1 illustrates the scatter plot of Kaohsiung County milkfish production versus year for the year of 1982-2008. A positive trend of milkfish production is identified and interpreted as technology improvement. Thus we remove the trend from milkfish production and examine the correlation between detrended milkfish production and annual average temperature (see Figure 2). The randomness plot pattern in Figure 2 implies that annual average temperature is not correlated with detrended milkfish production. In fact, this result does not bring us much surprise. According to Chang

4

(2004), and Chen et al. (2008), the appropriate temperature for milkfish ranges from 14°C to 43°C. Thus milkfish production should be sensitive to extreme low temperature rather than annual average temperature. In addition, most frost damages occur during January-March. So we take the minimum temperature of January-March each year and evaluate its relationship with detrended milkfish production. As Figure 3 shown, a positive correlation is presented between detrended milkfish production and minimum temperature of January-March. We also take logarithm of Kaohsiung County milkfish production and regress it on time trend, and annual average temperature and minimum temperature of January-March, respectively (see equations (1) and (2)).

$$\log Q_t = \alpha_0 + \alpha_1 t + \alpha_2 avgT_t + \varepsilon_t, \quad \varepsilon_t \sim iid(0, 1) \tag{1}$$

$$\log Q_t = \beta_0 + \beta_1 t + \beta_2 \min T^{123}{}_t + u_t, \quad u_t \sim iid(0, 1) \tag{2}$$

The estimation results in Table 1 are consistent with our previous findings that minimum temperature of January-March has statistically significant positive influence on milkfish production while annual average temperature does not. In other words, extreme low temperature in January-March is likely to result in poor milkfish production.


**Methodology**

Actuarial pricing methods for weather contracts depend upon correct specification of stationary time series of historical weather data. For number of reasons, however, it is fairly common to find gaps, jumps or absurd values in the historical data record. Thus, before the pricing methods can be applied, we must first check the data value to ascertain the stationary of data series and then identify the underlying process of climate data for properly data modeling and forecasting.

5

*Data Source and Sample Description*

In this study, we use the daily surface temperature data, which is collected and published by Central Weather Bureau, Taiwan, for a weather station located in Kaohsiung County. The Kaohsiung weather station was originally built back to the year of 1883 but was smashed during the war in 1895. After the reconstruction, it was moved to the current address on May 1, 1973. As noted by Jewson and Brix (2005), it is likely that the changes at meteorological stations could cause jumps in historical daily temperature data. In the worst scenario, the jumps can be up to several degree Centigrade and lead to severe mispricing of weather contract. Thus, the daily surface temperature data that we use for the study starts on 1974/01/01 and ends on 2008/12/31. Here we do not account for leap years.

Figure 4 illustrates Kaohsiung County daily average surface temperature for the period of 1974/01/01 – 2008/12/31, in which the daily average temperature is measured as the average of the daily maximum temperature and daily minimum temperature. As the figure exemplifies, the average daily temperature series plot reveals strong seasonality with small perturbations. That is, the daily average temperature fluctuation displays seasonal movement pattern of high temperature in summer and low temperature in winter. Besides, the seasonal cycle exists not only on the level of mean temperature but its variance. Figure 5 suggests that within a year, standard deviations of daily temperature in winter are more volatile than the ones in summer. Thus, we intend to use the Fourier series to model the seasonal components in daily average temperature and its variance. In addition, it is common to find that the annual minimum and maximum daily mean temperatures do not occur on January 1 and July 1. We can allow the peak of daily

average temperature to occur at any point in time within a year by introducing a phase angle in the low-order Fourier series (Alaton, Djehiche and Stillberger 2002).

Given a closer look at data series, we also identify a gradual positive trend in daily average temperature. To clearly reveal the trend, we plot Kaohsiung County annual average temperature versus year in Figure 6. The annual average temperature indeed increases over time. As indicated by Jewson and Brix (2005), there are many possible reasons for such trends. Here we suspect that urbanization and human-induced climate change are more likely to be possible causes of the trends in the historical Kaohsiung County daily average temperature. So we apply a simple low-ordered polynomial function to capture the deterministic trend. Finally, the temperature data exhibits cyclical dynamics as shown in Figure 7. The autoregressive lags are used to capture cyclical dynamics.

*Statistical Model*

Summing up all daily temperature components, we propose a nonlinear nonstructural time series approach to model and forecast Kaohsiung County daily average surface temperature. The model is constructed based on Campbell and Diebold (2005) as follows:

$$T_t = Trend_t + Seasonal_t + \sum_{l=1}^{L} \rho_{t-l} T_{t-l} + \sigma_t \varepsilon_t , \tag{1}$$

where

$$T_t = \frac{T_t^{\max} + T_t^{\min}}{2} ,$$

$$Trend_t = \sum_{m=0}^{M} \beta_m t^m , \tag{1a}$$

7

$$Seasonal_t = \sum_{p=1}^{P} \left( \sigma_{c,p} \cos\left( 2\pi p \frac{d(t)}{365} \right) + \sigma_{s,p} \sin\left( 2\pi p \frac{d(t)}{365} \right) \right), \tag{1b}$$

$$\sigma_t^2 = \sum_{q=1}^{Q} \left( \gamma_{c,q} \cos\left( 2\pi p \frac{d(t)}{365} \right) + \gamma_{c,q} \sin\left( 2\pi p \frac{d(t)}{365} \right) \right) + \sum_{r=1}^{R} \alpha_r \left( \sigma_{t-r} \varepsilon_{t-r} \right)^2 + \sum_{s=1}^{S} \beta_s \sigma_{t-s}^2, \tag{1c}$$

$$\varepsilon_t \sim iid(0,1),$$

and $d(t)$ is a repeating step function that cycles through 1, …, 365. As mentioned earlier, the annual minimum and maximum daily average temperature do not always occur on January 1 and July 1. Here we introduce a phase angle $\varphi$ in the low-order Fourier series of equation (1b). The equation (1b) can be rewritten as

$$Seasonal_t = \sum_{p=1}^{P} \left( \sigma_{c,p} \cos\left( 2\pi p \frac{d(t)}{365} \right) + \sigma_{s,p} \sin\left( 2\pi p \frac{d(t)}{365} + \varphi \right) \right). \tag{1b'}$$

Since the lower quantile of the daily average temperature risks is of our primary interest, the classical least-squares regression that models the conditional mean function may be inadequate to use. Alternative to Campbell and Diebold (2005), we model and forecast daily average temperature at its lower quantile rather than its mean values. The method that we use for this study is nonlinear quantile approach that models the quantiles of the conditional distribution of daily average temperature given the observed covariates (Koenker and Gillbert 1978; Hall, Wolff, Yao 1999; Koenker and Hallock 2000; Cai 2002; Chen, SAS). The algorithm for computing the nonlinear quantile regression estimates is based on an interior point method described in Koenker and Park (1996). Once the estimates are computed, we can invoke bootstrap method to resample the data series and price the proposed weather insurance contract (Hahn 1995).

**Statistical Results and Further Study**

8

As discussion thus far, we have obtained data of 1982-2008 Kaohsiung County Milkfish production from Council of Agriculture, Executive Yuan and data of 1960-2008 daily temperature in Kaohsiung County from Central Weather Bureau, Taiwan. We have found that extreme low temperature has significantly negative impacts on Milkfish production in Kaohsiung County. Our next plans for the study are to estimate the proposed model using the nonlinear quantile regression and to rate the temperature-based index insurance contract for the aquaculture industry in Taiwan.

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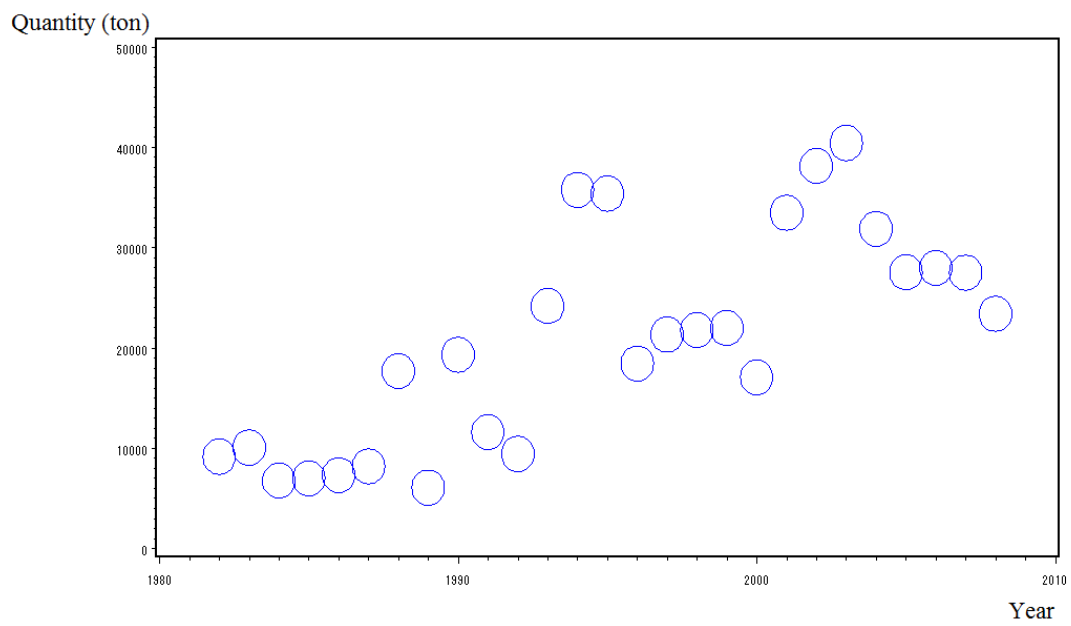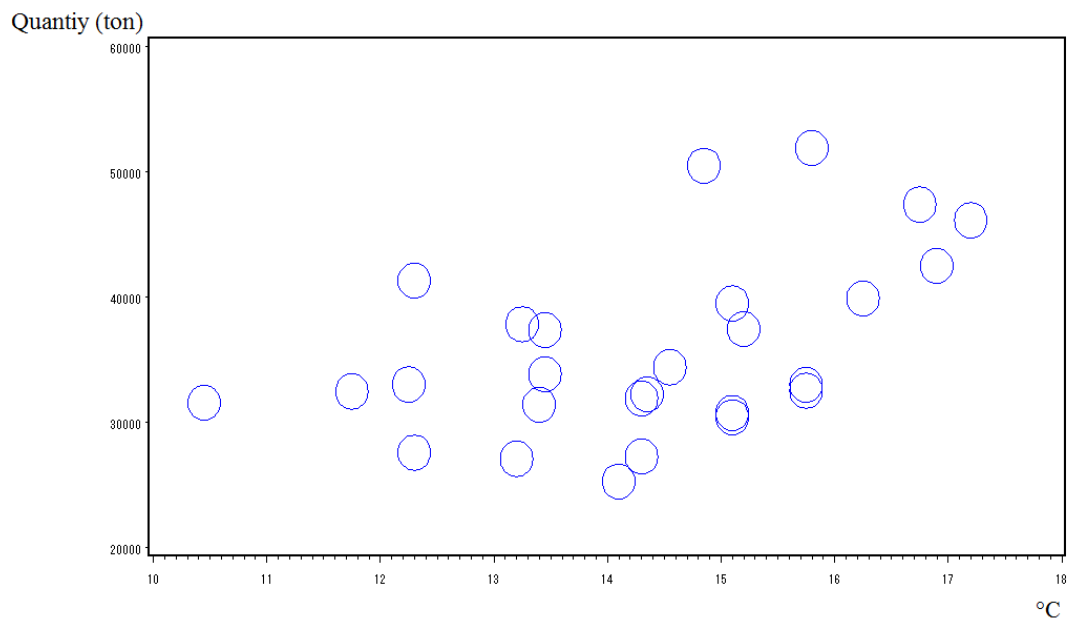
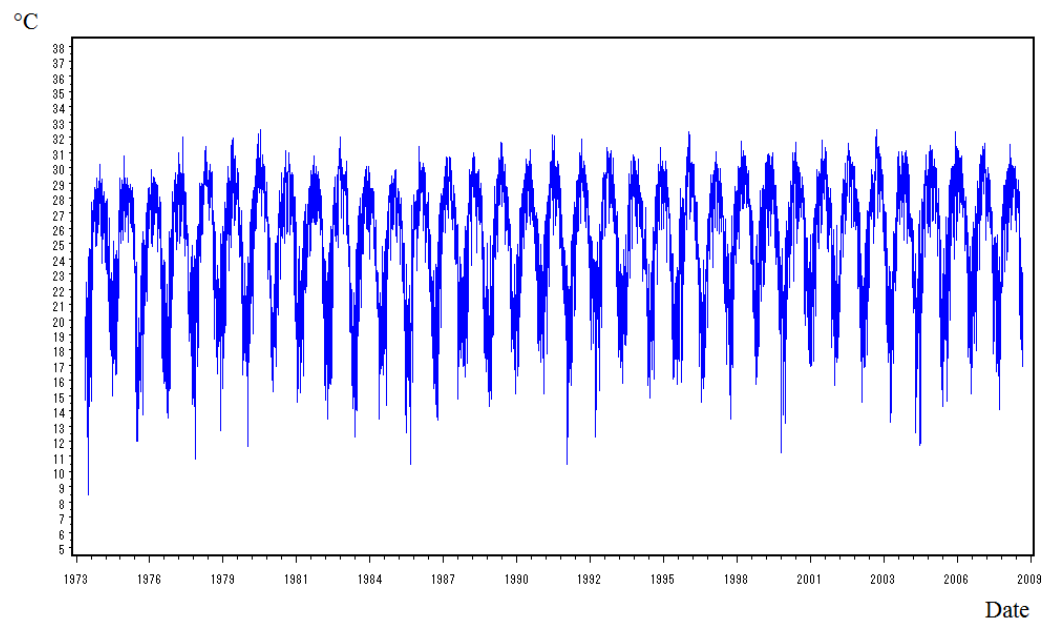**Figure 1. Scatter plot of milkfish production in Kaohsiung County vs. year, 1982 – 2008**
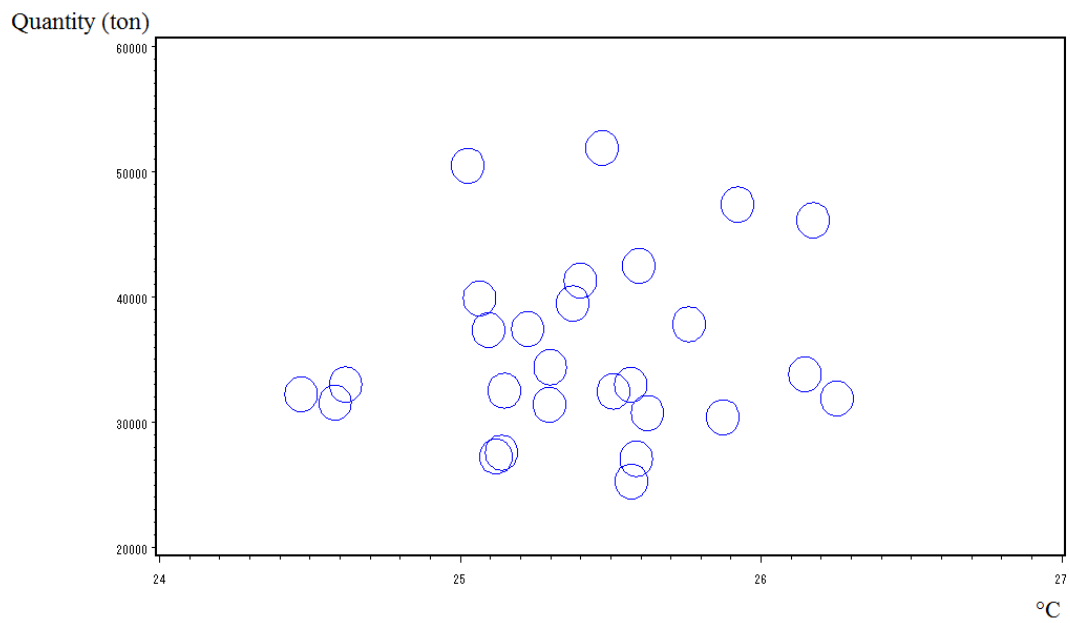
**Figure 2. Scatter plot of detrended production of milkfish in Kaohsiung County vs. annual average temperature, 1982 – 2008**
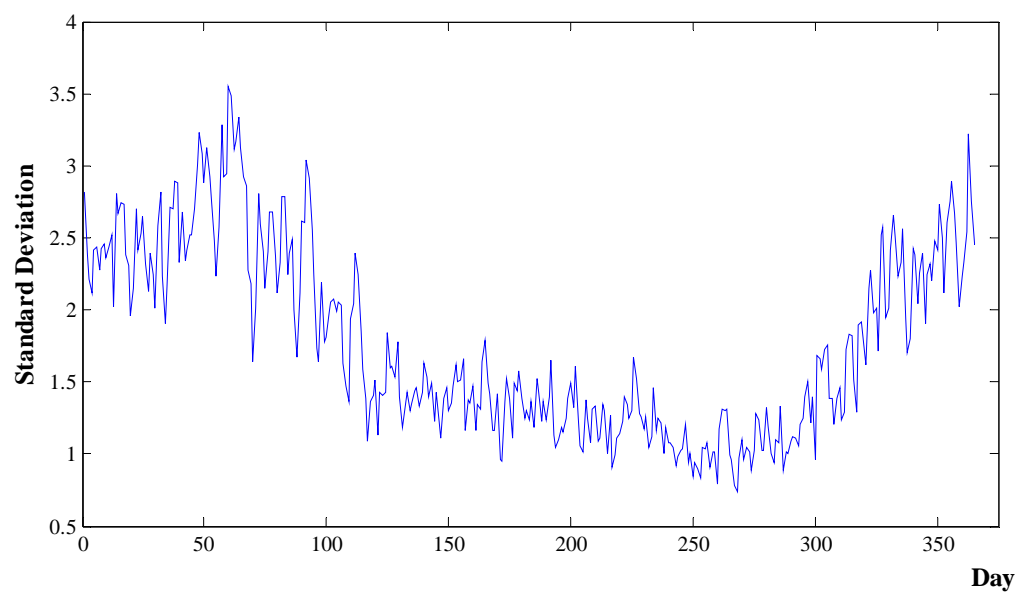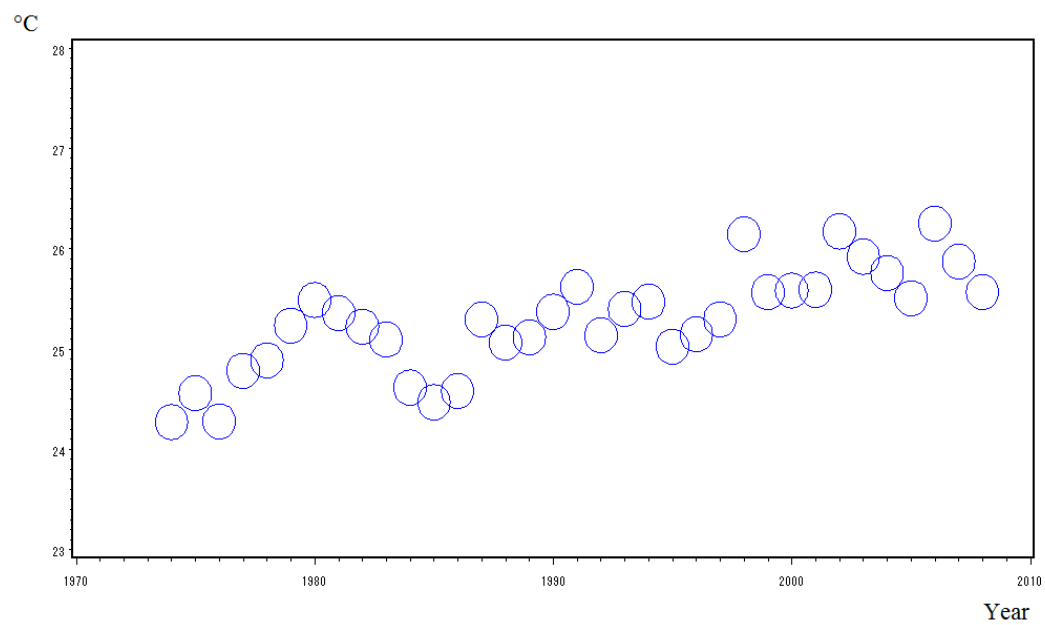
**Figure 3. Scatter plot of detrended production of milkfish in Kaohsiung County vs. minimum temperature of January – March, 1982 – 2008**
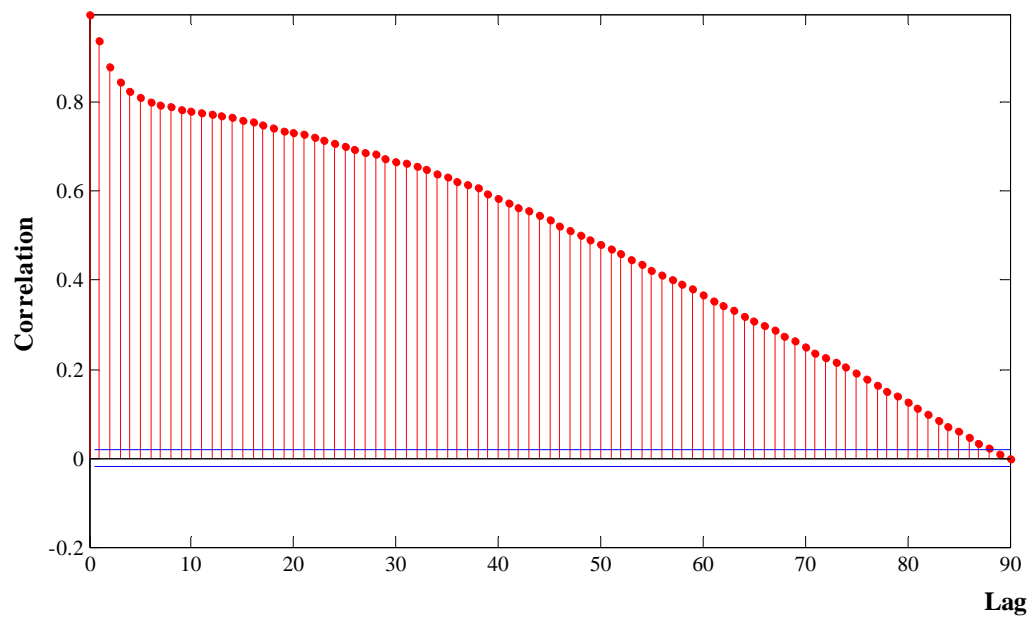
**Figure 4. Time series plots of daily average surface temperature in Kaohsiung County, 1974/01/01 – 2008/12/31**

**Figure 5. Estimated standard deviation of daily average surface temperature in Kaohsiung County, 1974/01/01 – 2008/12/31**

**Figure 6. Scatter plot of Kaohsiung County annual average temperature vs. year, 1974 – 2008**

**Figure 7. Autocorrelation functions for daily average surface temperature in Kaohsiung County, 1974/01/01 – 2008/12/31**

**Table 1. Estimation Results for Logarithm of Milkfish Quantity, 1982 – 2008**

Equation: $\log Q_t = cons\tan t + \beta_1 Trend + \beta_2 AvgT_t + \varepsilon_t$

| Variable | Parameter Estimate | Standard Error | P-value |
|---|---|---|---|
| Constant | 0.552 | 5.987 | 0.927 |
| Trend | 0.046* | 0.014 | 0.003 |
| Average Temperature | 0.324 | 0.245 | 0.199 |
| $R$-Square | 0.650 | | |
| Adjusted $R$-Sq | 0.620 | | |

Equation: $\log Q_t = cons\tan t + \beta_1 Trend + \beta_2 Minimum T^{123}_t + \varepsilon_t$

| Variable | Parameter Estimate | Standard Error | P-value |
|---|---|---|---|
| Constant | 6.959* | 0.570 | <.0001 |
| Trend | 0.055* | 0.009 | <.0001 |
| Minimum T-123 | 0.113* | 0.040 | 0.010 |
| $R$-Square | 0.716 | | |
| Adjusted $R$-Sq | 0.693 | | |